IMDB_Sentiment_Analysis

July 26, 2024

1 IMDB Sentiment Analysis

By Neuromatch Academy

Content creators: Mahdi Anvari, Hossein Ghermezcheshme, Sujal Awasthi, Harshil Shah

Production editors: Mahdi Anvari

[ ]:
```
# Import needed libraries
import pandas as pd
import numpy as np
import re
import torch
import torchtext
torchtext.disable_torchtext_deprecation_warning()
from torch.utils.data import DataLoader, Dataset
from torchtext.data.utils import get_tokenizer
from torchtext.vocab import build_vocab_from_iterator
from torch.nn.utils.rnn import pad_sequence
from sklearn.model_selection import train_test_split

import nltk
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from nltk.stem import PorterStemmer, WordNetLemmatizer
```

[ ]:
```
# Download necessary NLTK data files
nltk.download('punkt')
nltk.download('stopwords')
nltk.download('wordnet')
```

```
[nltk_data] Downloading package punkt to /root/nltk_data…
[nltk_data]   Unzipping tokenizers/punkt.zip.
[nltk_data] Downloading package stopwords to /root/nltk_data…
[nltk_data]   Unzipping corpora/stopwords.zip.
[nltk_data] Downloading package wordnet to /root/nltk_data…
```

[ ]:
```
True
```

Loading dataset

```
[ ]: # Import the dataset from google drive
from google.colab import drive
drive.mount('/content/drive')
df = pd.read_csv('/content/drive/My Drive/IMDBdataset.csv')
```

```
Mounted at /content/drive
```

```
[ ]: df.head()
```

```
[ ]:                                               review sentiment
0  One of the other reviewers has mentioned that …  positive
1  A wonderful little production. <br /><br />The…  positive
2  I thought this was a wonderful way to spend ti…  positive
3  Basically there's a family where a little boy …  negative
4  Petter Mattei's "Love in the Time of Money" is…  positive
```

```
[ ]: texts = df['review'].tolist()
labels = df['sentiment'].tolist()

label_map = {'positive': 1, 'negative': 0}
numeric_labels = [label_map[label] for label in labels]
numeric_labels = torch.tensor(numeric_labels)
```

Preprocessing steps

```
[ ]: # Text cleaning function
def clean_text(text):
    text = text.lower()  # Convert to lowercase
    text = re.sub(r'<.*?>', '', text)  # Remove HTML tags
    text = re.sub(r'[^\w\s]', '', text)  # Remove punctuation
    text = re.sub(r'\d+', '', text)  # Remove digits
    return text

# Tokenization function
def tokenize(text):
    return word_tokenize(text)

# Stop words removal function
def remove_stopwords(tokens):
    stop_words = set(stopwords.words('english'))
    return [word for word in tokens if word not in stop_words]

# Stemming function
def stem_tokens(tokens):
    stemmer = PorterStemmer()
    return [stemmer.stem(word) for word in tokens]

# Lemmatization function
```

```python
def lemmatize_tokens(tokens):
    lemmatizer = WordNetLemmatizer()
    return [lemmatizer.lemmatize(word) for word in tokens]

def preprocess(text):
    text = clean_text(text)
    tokens = tokenize(text)
    tokens = remove_stopwords(tokens)
    tokens = lemmatize_tokens(tokens)
    return ' '.join(tokens)

def preprocess_and_tokenize(text):
    text = clean_text(text)
    tokens = tokenize(text)
    tokens = remove_stopwords(tokens)
    tokens = lemmatize_tokens(tokens)
    return tokens
```

[ ]:
```python
df['cleaned_review'] = df['review'].apply(preprocess)
df.head()
```

[ ]:
```
                                              review sentiment  \
0  One of the other reviewers has mentioned that …  positive
1  A wonderful little production. <br /><br />The…  positive
2  I thought this was a wonderful way to spend ti…  positive
3  Basically there's a family where a little boy …  negative
4  Petter Mattei's "Love in the Time of Money" is…  positive

                                      cleaned_review
0  one reviewer mentioned watching oz episode you…
1  wonderful little production filming technique …
2  thought wonderful way spend time hot summer we…
3  basically there family little boy jake think t…
4  petter matteis love time money visually stunni…
```

Lets make an example

[ ]:
```python
sample_text = "I loved this movie! It was amazing, the acting was great and the␣
↪plot was very exciting."
print(sample_text)
print(preprocess(sample_text))
print(preprocess_and_tokenize(sample_text))
```

```
I loved this movie! It was amazing, the acting was great and the plot was very
exciting.
loved movie amazing acting great plot exciting
['loved', 'movie', 'amazing', 'acting', 'great', 'plot', 'exciting']
```

[ ]:
```
preprocessed_tokens = [preprocess_and_tokenize(text) for text in texts]
```

Building vocabulary

[ ]:
```
# Build vocabulary from the tokenized texts
from collections import Counter
def yield_tokens(data_iter):
    for tokens in data_iter:
        yield tokens

vocab = build_vocab_from_iterator(yield_tokens(preprocessed_tokens),␣
 ↪specials=["<unk>"])
vocab.set_default_index(vocab["<unk>"])
```

[ ]:
```
words = Counter()
for s in preprocessed_tokens:
  for w in s:
    words[w] += 1

sorted_words = list(words.keys())
sorted_nums = list(words.values())
sorted_words.sort(key=lambda w: words[w], reverse=True)
sorted_nums.sort(reverse=True)
print(f"Number of different reviews in our dataset: {len(preprocessed_tokens)}")
print(f"Number of different tokens in our dataset: {len(sorted_words)}")
print("Top 100 tokens and their frequencies:")
print(sorted_words[:100])
print(sorted_nums[:100])
```

```
Number of different reviews in our dataset: 50000
Number of different tokens in our dataset: 203664
Top 100 tokens and their frequencies:
['movie', 'film', 'one', 'like', 'time', 'good', 'character', 'get', 'even',
'story', 'would', 'make', 'see', 'really', 'scene', 'much', 'well', 'people',
'great', 'bad', 'also', 'show', 'first', 'dont', 'way', 'thing', 'made',
'could', 'think', 'life', 'go', 'know', 'watch', 'love', 'many', 'seen',
'actor', 'two', 'plot', 'say', 'never', 'look', 'acting', 'end', 'little',
'best', 'year', 'ever', 'better', 'take', 'man', 'come', 'still', 'work',
'part', 'find', 'something', 'want', 'give', 'lot', 'back', 'director', 'im',
'real', 'guy', 'watching', 'doesnt', 'performance', 'didnt', 'play', 'woman',
'actually', 'though', 'funny', 'another', 'nothing', 'going', 'role', 'u',
'new', 'old', 'every', 'girl', 'cant', 'point', 'cast', 'world', 'fact',
'thats', 'quite', 'day', 'got', 'pretty', 'feel', 'minute', 'thought', 'seems',
'around', 'young', 'comedy']
[98839, 89766, 52616, 39736, 29359, 28582, 27539, 24395, 24264, 24204, 23974,
23527, 23469, 22856, 20667, 18874, 18607, 17963, 17769, 17654, 17471, 16864,
16827, 16607, 16515, 16051, 15399, 15126, 15065, 14381, 14263, 14047, 13666,
13352, 13254, 13090, 12997, 12920, 12881, 12842, 12826, 12561, 12397, 12317,
```

```
12296, 12286, 12263, 11620, 11041, 11024, 10986, 10856, 10649, 10400, 9965,
9940, 9809, 9771, 9678, 9577, 9282, 9025, 9004, 8989, 8925, 8913, 8862, 8803,
8786, 8661, 8632, 8351, 8333, 8307, 8174, 8161, 8066, 8039, 8017, 7953, 7860,
7854, 7495, 7476, 7337, 7289, 7269, 7248, 7212, 7210, 7179, 7175, 7153, 7153,
7143, 7061, 7039, 6975, 6949, 6913]
```

[ ]:
```
print(sum(sorted_nums[:100]))
print(sum(sorted_nums))
print(sum(sorted_nums[:100])/sum(sorted_nums))
```

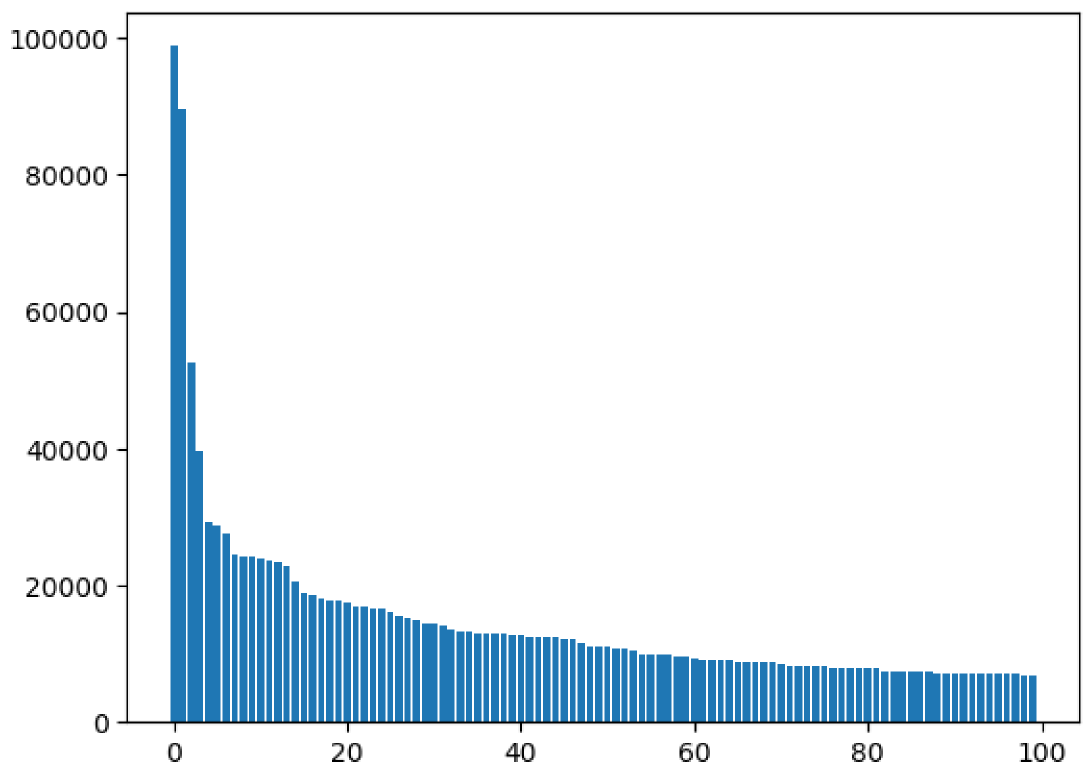
```
1476813
5923292
0.24932301159557896
```

interesting!

[ ]:
```
print(sorted_nums[sorted_words.index("deep")])
print(sorted_nums[sorted_words.index("learning")])
```

```
1345
327
```

[ ]:
```
import matplotlib.pyplot as plt
plt.bar(range(100), [words[w] for w in sorted_words[:100]])
plt.show()
```



Now, lets vectorize the samples

[ ]:
```
from sklearn.feature_extraction.text import TfidfVectorizer

# Initialize TF-IDF vectorizer
vectorizer = TfidfVectorizer(max_features=10000)

# Fit and transform the cleaned reviews
X = vectorizer.fit_transform(df['cleaned_review']).toarray()
Y = df['sentiment'].apply(lambda x: 1 if x == 'positive' else 0).values
```

[ ]:
```
def check_nonzero_features(x):
  nonzero = x[x != 0]
  print("Number of nonzero features:" , len(nonzero))
  print((nonzero))
  # You can also get the index of nonzero features
  # print([index for index, value in enumerate(o != 0) if value])
```

[ ]:
```
print(check_nonzero_features(X[0]))
```

```
Number of nonzero features: 123
[0.1028663  0.08938036 0.09996118 0.06715452 0.04167847 0.04649839
 0.04470474 0.05240101 0.09301927 0.09206266 0.05372835 0.07936075
 0.06829412 0.07380269 0.11454489 0.06091616 0.04895462 0.08506192
 0.05152562 0.09697236 0.0796384  0.08619639 0.07369995 0.04986384
 0.07027094 0.09727299 0.03905411 0.06374907 0.11700578 0.08619639
 0.10542281 0.03531657 0.05721346 0.05458655 0.08971955 0.04972946
 0.04126449 0.09583381 0.0439792  0.06383301 0.06279554 0.18426631
 0.06324049 0.05617086 0.04996127 0.07580308 0.06672387 0.04117884
 0.07046985 0.07819674 0.05725767 0.08429915 0.09258555 0.09847475
 0.05045067 0.08264021 0.09516898 0.19112771 0.08209823 0.0681925
 0.05215281 0.05299178 0.10092711 0.05636576 0.0471662  0.06920914
 0.07916594 0.1028663  0.09610939 0.04297925 0.06543121 0.06372498
 0.09742591 0.06015037 0.09324159 0.07170853 0.03463598 0.10310042
 0.02085851 0.05680063 0.44167246 0.08758273 0.05078579 0.04196571
 0.21401872 0.06467287 0.07686434 0.07100147 0.0771934  0.06692259
 0.08484366 0.04260098 0.06912555 0.03117277 0.0772602  0.08063717
 0.04346457 0.05387615 0.09996118 0.14306134 0.05387615 0.06884968
 0.08148509 0.08743737 0.05986863 0.0606083  0.16578821 0.07739483
 0.06583439 0.03224883 0.06262831 0.07254901 0.05815868 0.08310079
 0.04990188 0.23453316 0.04676282 0.07686653 0.03049496 0.05000386
 0.02841404 0.05608584 0.05414174]
None
```

Split the dataset

[ ]:
```
from sklearn.model_selection import train_test_split

# Split the data
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.5)
```

[ ]:
```
del X
del Y
```

[ ]:
```
import gc
gc.collect()
```

[ ]: 0

2 Implementation

Logistic Regression

[ ]:
```
from sklearn.linear_model import LogisticRegression
LR_model = LogisticRegression(solver='saga')
LR_model.fit(X_train, Y_train)
```

[ ]: LogisticRegression(solver='saga')

[ ]:
```
from sklearn.metrics import classification_report, accuracy_score
Y_pred_LR = LR_model.predict(X_test)
print(classification_report(Y_test, Y_pred_LR))
LR_acc = accuracy_score(Y_test , Y_pred_LR)
print(LR_acc)
```

```
              precision    recall  f1-score   support

           0       0.89      0.87      0.88     12582
           1       0.88      0.89      0.88     12418

    accuracy                           0.88     25000
   macro avg       0.88      0.88      0.88     25000
weighted avg       0.88      0.88      0.88     25000

0.88416
```

Multi Layer Perceptron

[ ]:
```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.optimizers import Adam
from tensorflow.keras import regularizers
```

```python
MLP_model = Sequential()
MLP_model.add(Dense(128, input_dim=X_train.shape[1], activation='relu',␣
 ↪kernel_regularizer=regularizers.l2(0.001)))
MLP_model.add(Dropout(0.5))
MLP_model.add(Dense(64, activation='relu', kernel_regularizer=regularizers.l2(0.
 ↪001)))
MLP_model.add(Dropout(0.2))
MLP_model.add(Dense(32, activation='relu', kernel_regularizer=regularizers.l2(0.
 ↪0001)))
MLP_model.add(Dense(1, activation='sigmoid'))

MLP_model.compile(loss='binary_crossentropy',
              optimizer=Adam(learning_rate=0.004),
              metrics=['accuracy'])

history = MLP_model.fit(X_train, Y_train,
                    epochs=7,
                    batch_size=32,
                    validation_split=0.2,
                    verbose=1)
```

```
Epoch 1/7
625/625 [==============================] - 29s 45ms/step - loss: 0.7933 -
accuracy: 0.8288 - val_loss: 0.8236 - val_accuracy: 0.8560
Epoch 2/7
625/625 [==============================] - 20s 32ms/step - loss: 0.8184 -
accuracy: 0.8521 - val_loss: 0.7974 - val_accuracy: 0.8574
Epoch 3/7
625/625 [==============================] - 20s 33ms/step - loss: 0.8242 -
accuracy: 0.8590 - val_loss: 0.8167 - val_accuracy: 0.8406
Epoch 4/7
625/625 [==============================] - 20s 33ms/step - loss: 0.7997 -
accuracy: 0.8578 - val_loss: 0.7926 - val_accuracy: 0.8548
Epoch 5/7
625/625 [==============================] - 23s 36ms/step - loss: 0.7907 -
accuracy: 0.8571 - val_loss: 0.7439 - val_accuracy: 0.8666
Epoch 6/7
625/625 [==============================] - 23s 36ms/step - loss: 0.7742 -
accuracy: 0.8561 - val_loss: 0.7358 - val_accuracy: 0.8618
Epoch 7/7
625/625 [==============================] - 21s 34ms/step - loss: 0.7676 -
accuracy: 0.8589 - val_loss: 0.7231 - val_accuracy: 0.8624
```

[ ]:
```python
test_loss, test_accuracy = MLP_model.evaluate(X_test, Y_test, verbose=0)
print(f'Test Accuracy: {test_accuracy:.4f}')
```

```
Test Accuracy: 0.8655
```

Convolutional Neural Network

[ ]:
```
import numpy as np
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv1D, MaxPooling1D, Flatten, Dense,␣
↪Dropout
from tensorflow.keras.optimizers import Adam

# Reshape X_train to fit the input shape of Conv1D
X_train_cnn = X_train.reshape(X_train.shape[0], X_train.shape[1], 1)

CNN_model = Sequential()
CNN_model.add(Conv1D(32, 5, activation='relu', input_shape=(10000, 1)))
CNN_model.add(MaxPooling1D(pool_size=2))
CNN_model.add(Conv1D(64, 5, activation='relu'))
CNN_model.add(MaxPooling1D(pool_size=2))
CNN_model.add(Flatten())
CNN_model.add(Dense(128, activation='relu'))
CNN_model.add(Dropout(0.5))
CNN_model.add(Dense(1, activation='sigmoid'))
CNN_model.compile(optimizer=Adam(learning_rate=0.001),␣
↪loss='binary_crossentropy', metrics=['accuracy'])
CNN_model.fit(X_train_cnn, Y_train, epochs=2, batch_size=32, validation_split=0.
↪2)
```

```
Epoch 1/2
625/625 [==============================] - 862s 1s/step - loss: 0.3794 -
accuracy: 0.8278 - val_loss: 0.3154 - val_accuracy: 0.8612
Epoch 2/2
625/625 [==============================] - 874s 1s/step - loss: 0.2336 -
accuracy: 0.9036 - val_loss: 0.3191 - val_accuracy: 0.8662
```

[ ]:
```
<keras.src.callbacks.History at 0x7dc58cf76ad0>
```

[ ]:
```
# Evaluate the model
X_test_cnn = X_test.reshape(X_test.shape[0], X_test.shape[1], 1)

loss, accuracy = CNN_model.evaluate(X_test_cnn, Y_test, verbose=2)
print(f'Test Accuracy: {accuracy:.4f}')
```

```
782/782 - 193s - loss: 0.3113 - accuracy: 0.8712 - 193s/epoch - 246ms/step
Test Accuracy: 0.8712
```

Recurrent Neural Nrtwork

[ ]:
```
# Reshape the data to have time steps and features per time step
sequence_length = 1
num_features = 10000
```

```
X_train_RNN = X_train.reshape((25000, sequence_length, num_features))
X_test_RNN = X_test.reshape((25000, sequence_length, num_features))

import numpy as np
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import SimpleRNN, Dense
from tensorflow.keras.optimizers import Adam

RNN_model = Sequential()
RNN_model.add(SimpleRNN(400, input_shape=(1, 10000), return_sequences=False))
RNN_model.add(Dense(1, activation='sigmoid'))
RNN_model.compile(optimizer=Adam(learning_rate=0.0001),␣
↪loss='binary_crossentropy', metrics=['accuracy'])
RNN_model.fit(X_train_RNN, Y_train, epochs=5, batch_size=32, validation_split=0.
↪2)
```

```
Epoch 1/5
625/625 [==============================] - 62s 95ms/step - loss: 0.5504 -
accuracy: 0.8286 - val_loss: 0.4107 - val_accuracy: 0.8682
Epoch 2/5
625/625 [==============================] - 63s 101ms/step - loss: 0.3204 -
accuracy: 0.8954 - val_loss: 0.3058 - val_accuracy: 0.8816
Epoch 3/5
625/625 [==============================] - 58s 93ms/step - loss: 0.2325 -
accuracy: 0.9209 - val_loss: 0.2796 - val_accuracy: 0.8838
Epoch 4/5
625/625 [==============================] - 64s 102ms/step - loss: 0.1876 -
accuracy: 0.9369 - val_loss: 0.2735 - val_accuracy: 0.8836
Epoch 5/5
625/625 [==============================] - 61s 98ms/step - loss: 0.1572 -
accuracy: 0.9485 - val_loss: 0.2788 - val_accuracy: 0.8830
```

[ ]: <keras.src.callbacks.History at 0x7dc58e304c40>

[ ]:
```
loss, accuracy = RNN_model.evaluate(X_test_RNN, Y_test, verbose=2)
print(f'Test Accuracy: {accuracy:.4f}')
```

```
782/782 - 11s - loss: 0.2711 - accuracy: 0.8895 - 11s/epoch - 14ms/step
Test Accuracy: 0.8895
```

Long Short-Term Memory

[ ]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout

sequence_length = 1
num_features = 10000

X_train_LSTM = X_train.reshape((25000, sequence_length, num_features))
```

```
X_test_LSTM = X_test.reshape((25000, sequence_length, num_features))

LSTM_model = Sequential()
LSTM_model.add(LSTM(300, input_shape=(sequence_length, num_features),␣
 ↪return_sequences=False))
LSTM_model.add(Dropout(0.5))
LSTM_model.add(Dense(1, activation='sigmoid'))
LSTM_model.compile(optimizer='adam', loss='binary_crossentropy',␣
 ↪metrics=['accuracy'])
LSTM_model.fit(X_train_LSTM, Y_train, epochs=5, batch_size=32,␣
 ↪validation_split=0.2)
```

```
Epoch 1/5
625/625 [==============================] - 231s 367ms/step - loss: 0.3642 -
accuracy: 0.8579 - val_loss: 0.2761 - val_accuracy: 0.8822
Epoch 2/5
625/625 [==============================] - 237s 379ms/step - loss: 0.1823 -
accuracy: 0.9309 - val_loss: 0.3051 - val_accuracy: 0.8742
Epoch 3/5
625/625 [==============================] - 241s 386ms/step - loss: 0.1278 -
accuracy: 0.9549 - val_loss: 0.3658 - val_accuracy: 0.8690
Epoch 4/5
625/625 [==============================] - 236s 377ms/step - loss: 0.0921 -
accuracy: 0.9702 - val_loss: 0.4489 - val_accuracy: 0.8578
Epoch 5/5
625/625 [==============================] - 232s 372ms/step - loss: 0.0646 -
accuracy: 0.9801 - val_loss: 0.5330 - val_accuracy: 0.8536
```

```
[ ]: <keras.src.callbacks.History at 0x7dc58d86d060>
```

```
[ ]: loss, accuracy = LSTM_model.evaluate(X_test_LSTM, Y_test, verbose=2)
     print(f'Test Accuracy: {accuracy:.4f}')
```

```
782/782 - 28s - loss: 0.5262 - accuracy: 0.8606 - 28s/epoch - 36ms/step
Test Accuracy: 0.8606
```

BERT

```
[ ]: from transformers import AutoTokenizer, AutoModelForSequenceClassification
     import torch
```

```
[ ]: model_name = "distilbert-base-uncased-finetuned-sst-2-english"
     tokenizer = AutoTokenizer.from_pretrained(model_name)
     model = AutoModelForSequenceClassification.from_pretrained(model_name)
```

```
[ ]: def analyze_sentiment(review):
         inputs = tokenizer(review, return_tensors="pt", truncation=True,␣
      ↪padding=True, max_length=512)
         with torch.no_grad():
```

```
        outputs = model(**inputs)
    logits = outputs.logits
    probabilities = torch.nn.functional.softmax(logits, dim=-1)
    predicted_class = torch.argmax(probabilities, dim=-1).item()
    labels = ["negative", "positive"]
    predicted_label = labels[predicted_class]
    return predicted_label
```

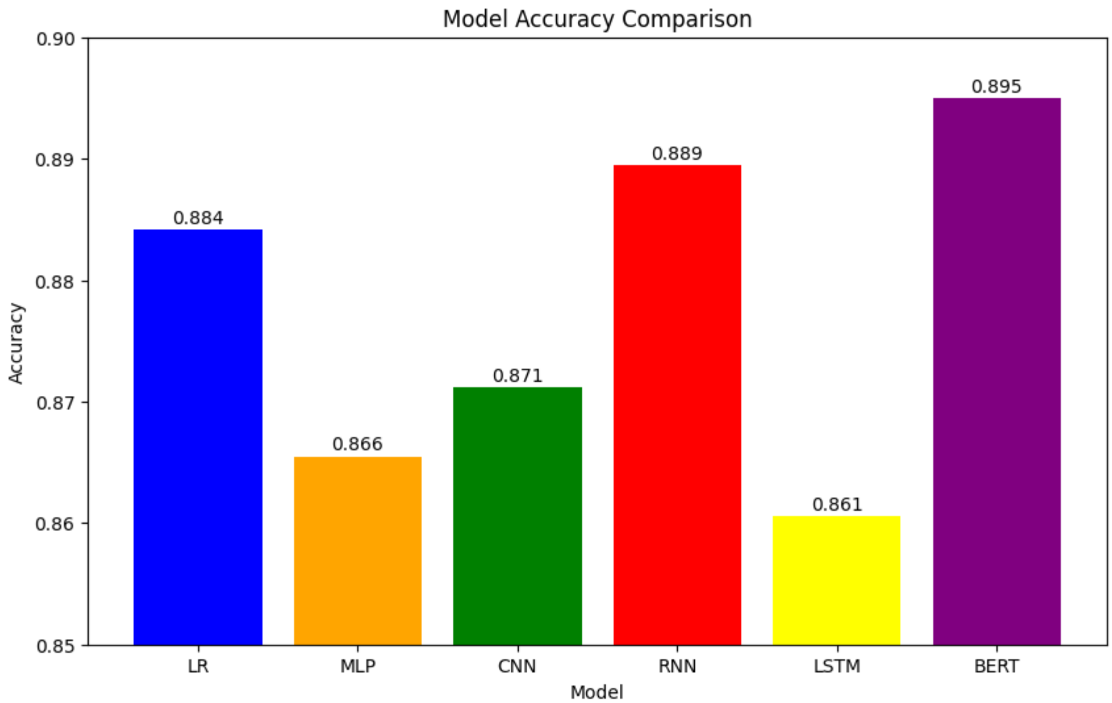
[ ]:
```
sample_data = df.sample(5000)
y_pred = sample_data['review'].apply(analyze_sentiment)
y = sample_data['sentiment']
accuracy = (y_pred == y).mean()
print("Average Accuracy by BERT uncased model:", accuracy)
```

```
Average Accuracy by BERT uncased model: 0.895
```

Comparison

[ ]:
```
import matplotlib.pyplot as plt
data = {
    'Model': ['LR' , 'MLP', 'CNN' , 'RNN' , 'LSTM' , 'BERT'],
    'Accuracy': [0.88416, 0.8655, 0.8712, 0.8895, 0.8606, 0.8950]
}

# Bar Plot
plt.figure(figsize=(10, 6))
plt.bar(data['Model'], data['Accuracy'], color=['blue' , 'orange' , 'green' ,
 ↪'red' , 'yellow' , 'purple'])
for index, value in enumerate(data['Accuracy']):
    plt.text(index, value + 0.0005, f'{value:.3f}', ha='center')
plt.xlabel('Model')
plt.ylabel('Accuracy')
plt.title('Model Accuracy Comparison')
plt.ylim(0.85, 0.90)
plt.show()
```


Model Accuracy Comparison
0.90
0.89
0.88
0.87
0.86
0.85
Accuracy
0.884
0.866
0.871
0.889
0.861
0.895
LR
MLP
CNN
RNN
LSTM
BERT
Model